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Multi-Objective Wireless Resource Management Optimization Framework Based on NSGA-II and Whale Optimization Algorithm

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Abstract: This study addresses multi-objective optimization problems in wireless resource management by proposing a novel framework combining NSGA-II and the Whale Optimization Algorithm (WOA). By simultaneously optimizing multiple objectives, including quality of service, energy efficiency, and interference mitigation, this framework effectively addresses resource allocation and power control in multi-slice environments. Experimental results demonstrate that the proposed optimization method excels across multiple performance metrics, particularly demonstrating flexibility and efficiency when addressing trade-offs between different objectives. Compared to traditional optimization algorithms, the combination of NSGA-II and WOA offers significant advantages in solving multi-objective problems and possesses strong practicality and application potential.

1. Introduction

In this study, we focus on modeling and solving multi-objective optimization problems in wireless resource management. Wireless resource management involves rationally allocating resources under limited spectrum and power constraints to meet the performance requirements of different service classes [1]. To address this challenge, we propose a resource allocation method based on a multi-objective optimization framework, combining the NSGA-II algorithm, Whale Optimization Algorithm (WOA), and an integer programming model (EPS) for solution [2]. This approach aims to identify a reasonable resource allocation scheme by optimizing multiple objectives—such as Quality of Service (QoS), energy efficiency, and interference control—to enhance overall system performance [3].

The core challenge in wireless resource management lies in simultaneously considering multiple performance metrics [4]. QoS, a critical indicator in resource allocation, primarily encompasses latency, throughput, and reliability. Different service classes demand varying levels of these performance metrics [5]. For instance, URLLC services demand ultra-low latency and high reliability, eMBB services prioritize throughput enhancement, while mMTC services focus on connecting massive devices and optimizing energy efficiency [6]. Thus, balancing these objectives presents a significant challenge in wireless resource management. Multi-objective optimization approaches provide feasible solutions by simultaneously optimizing multiple goals and identifying optimal trade-offs among them [7].

In this study, the NSGA-II algorithm is employed to address the multi-objective optimization problem. As a genetic algorithm-based approach, NSGA-II effectively handles conflicts among different objectives through non-domination sorting and crowding degree calculations. Within wireless resource management, NSGA-II can simultaneously optimize multiple objectives such as service quality, energy efficiency, and interference control, yielding a set of solutions with favorable trade-offs that constitute the problem's Pareto front. The advantage of NSGA-II lies in its ability to find reasonable compromises among multiple objectives, ensuring each objective receives adequate optimization. We applied the NSGA-II algorithm to optimize resource allocation in network slicing, enabling each slice to minimize energy consumption and interference while meeting its service requirements.

However, despite its strong performance in multi-objective optimization, the NSGA-II algorithm still faces challenges when solving wireless resource management problems. To overcome these issues, we introduce the Whale Optimization Algorithm (WOA). WOA is a heuristic optimization algorithm inspired by the hunting behavior of humpback whales, combining global and local search capabilities. In wireless resource scheduling problems, WOA helps optimize power control and resource allocation to reduce system interference and enhance overall performance. By simulating whales' swimming patterns around prey and bubble net attacks, WOA provides an effective global search mechanism that prevents the algorithm from getting stuck in local optima. We combine WOA with NSGA-II, leveraging WOA to optimize power control and resource allocation. This approach further enhances the system's energy efficiency and interference suppression capabilities while ensuring quality of service.

Beyond employing NSGA-II and WOA for resource allocation, this study incorporates an EPS to address discrete resource allocation challenges. In practical applications, resource blocks (RBs) serve as fundamental allocation units in wireless communications, exhibiting discrete characteristics. Thus, we adopt an integer programming approach for resource allocation. The EPS model enumerates and prunes RBs to identify optimal allocation schemes while satisfying all constraints. The EPS model also accounts for each slice's minimum occupancy requirement and quality-of-service objectives, ensuring rational resource allocation. In this study, the EPS model will be integrated with NSGA-II and WOA algorithms to provide an effective multi-objective optimization solution.

In summary, this study employs a multi-objective optimization framework integrating the NSGA-II algorithm, Whale Optimization Algorithm (WOA), and the integer programming model (EPS) to address multi-objective optimization challenges in wireless resource management. By optimizing multiple objectives including service quality, energy efficiency, and interference control, the proposed resource allocation method enhances overall system performance while accommodating diverse service requirements. Subsequent sections will detail problem modeling, algorithm design, and experimental results.

2. Problem Definition and Modeling

In a multi-slice wireless network scenario, multiple types of services (such as URLLC, eMBB, and mMtc) run in parallel while sharing limited resources, including RBs and transmit power. Each service slice has distinct QOS requirements: URLLC demands ultra-low latency and high reliability, eMBB emphasizes high throughput, and mMTC focuses on massive connectivity and access success rate [8]. Therefore, it is necessary to build a unified optimization model that jointly considers QoS assurance, energy consumption control, and interference suppression, to achieve global performance maximization through efficient resource scheduling and allocation [9].

This study formulates the resource management problem as a multi-objective optimization task involving three decision variables: RB allocation, power control, and user association [10]. Let the base station set be B={1,2,…,B}, the slice set be S={"URLLC","eMBB","mMTC"}, and the user set be U [11]. Each base station b∈B has a fixed number of allocatable RBs, constrained by:

$$\sum_{s \in \mathrm{S}} x_{b,s} \le R_b^{\mathrm{tot}}, \quad \forall b \in \mathrm{B} \tag{1}$$

Here, $x_{b,s}$ denotes the number of RBs assigned by base station b to slice s. To model transmission performance and interference, let $h_{b,u}$ represent the channel gain from base station b to user u, and let $b(u)$ denote the base station serving user u [12]. The signal-to-interference-plus-noise ratio (SINR) is defined as:

$$\mathrm{SINR}_u = \frac{p_{b(u),s(u)} \cdot h_{b(u),u}}{\sigma^2 + \sum_{b' \neq b(u)} \rho_{b',s(u)} \cdot p_{b',s(u)} \cdot h_{b',u}} \tag{2}$$

Where $\rho_{b',s}$ is the RB overlap ratio between base stations (modeling expected interference), and σ^2 is the noise power [13].

The nominal transmission rate per RB is given by:

$$r_{b,s}^{\mathrm{RB}} = \beta_s \cdot B \cdot \log_2\left(1 + \mathrm{SINR}_{b,s}\right) \tag{3}$$

Where $\beta_s \in (0,1]$ is the encoding efficiency of slice s, and B is the bandwidth per RB.

Given that each user u requires a demand of d_u within a scheduling window, the total served data volume for slice s at base station b is [14]:

$$y_{b,s} = x_{b,s} \cdot r_{b,s}^{\mathrm{RB}} \cdot \Delta t \tag{4}$$

In the proposed multi-objective optimization framework, we jointly consider the following four objectives:

$$f_1 = \sum_{s \in \mathrm{S}} \omega_s \cdot \min\left(1, \frac{y_s}{d_s}\right) \tag{5}$$

Where ω_s is the weight for slice s, y_s is the total served volume, and d_s is the total demand for slice s.

$$f_2 = \sum_{s \in \mathrm{S}} \sum_{b \neq b'} \rho_{b,s} \cdot \rho_{b',s} \cdot p_{b,s} \cdot h_{b',s} \tag{6}$$

$$f_3 = \sum_{b \in \mathrm{B}} \sum_{s \in \mathrm{S}} \left(P_{\mathrm{fix}} + \frac{p_{b,s} \cdot x_{b,s}}{\eta}\right) \tag{7}$$

Where P_{fix} is the fixed power consumption, and η is the power amplifier efficiency.

$$f_4 = \frac{\left(\sum_{s\in S} z_s\right)^2}{|S| \cdot \sum_{s\in S} z_s^2}, \quad z_s = \min\left(1, \frac{y_s}{d_s}\right) \tag{8}$$

As the above objectives are conflicting, a multi-objective evolutionary algorithm (MOEA) is required for balanced optimization [15].

To solve this, two algorithms are introduced:

NSGA-II: A genetic algorithm that uses non-dominated sorting and crowding distance to obtain a Pareto front. WOA: A metaheuristic algorithm inspired by whale hunting behavior, capable of global search and efficient exploitation.

The optimization process adopts a two-level hybrid architecture: Outer loop: NSGA-II determines RB allocation $x_{b,s}$ And user association $a_{u,b}$; Inner loop: WOA optimizes power allocation $p_{b,s}$, updates interference, and recalculates $y_{b,s}$.

The final model outputs a set of Pareto-optimal solutions, offering trade-offs such as best qos, lowest energy, or best fairness, suitable for real-world wireless deployment.

3. Methods and Algorithms

This chapter details the three main methods used in this paper: the NSGA-II, the WOA, and the EPS. Furthermore, a multi-objective optimization framework is constructed to collaboratively optimize multiple objectives, including resource allocation, power control, quality of service, energy consumption, and interference.

3.1 Application of NSGA-II in Resource Scheduling

NSGA-II is a classical multi-objective optimization algorithm widely used in solving multi-objective problems. This algorithm adopts the idea of evolutionary computation and uses genetic operations (selection, crossover, and mutation) to explore the solution space by simulating natural selection.

In this study, NSGA-II is used to optimize resource allocation and scheduling decisions, with specific decision variables being the resource block allocation $x_{b,s}$ and user association $a_{u,b}$. The process is as follows:

The process is as follows: Initial Population: Randomly generate a population, where each individual in the population represents a solution including resource allocation and user association decisions. Objective Calculation: According to the model in the second chapter, the service quality, interference, energy consumption, and fairness goals of each solution are calculated. Non-dominated Sorting: All solutions in the population are sorted based on their non-dominated relationships to identify the Pareto front. Crowding Distance: For each front, the crowding distance of each solution is calculated to maintain diversity in the solution set. Selection: Select individuals based on the fitness of their solutions to produce a new generation. Crossover and Mutation: Perform genetic operations like crossover and mutation to generate offspring individuals.

This method outputs a set of Pareto-optimal solutions, offering various solutions for resource allocation that emphasize different objectives, such as prioritizing service quality or optimizing energy consumption.

3.2 Application of WOA in Power Control

WOA is a global optimization algorithm inspired by the hunting behavior of humpback whales, which simulate "bubble-net attacking" behavior to search for optimal positions. It consists of three main strategies: encircling prey, spiral updating, and searching randomly.

In this study, woa is used to optimize the power variable $p_{b,s}$, specifically for controlling interference and energy consumption under the resource allocation scheme generated by nsga-ii. The steps in woa for power control are as follows:

Initialization of whale position: each individual in the population represents a power allocation strategy. Evaluation of fitness: the fitness of each whale is calculated by evaluating the current resource allocation, and the corresponding power control strategy is considered.

Position update: if encircling the prey is selected: the whale moves towards the best solution found so far. If the spiral movement strategy is selected: the whale moves in a spiral path around the best solution. If random exploration is selected: the whale explores a new area in the solution space. Finalization of optimal solution: the search continues until the optimal solution meets the predefined stopping criteria.

Woa is used here as an inner optimization process, and it can efficiently find the power control strategy that closely approximates the optimal solution, thus enhancing the overall performance of the resource allocation strategy by improving power control and reducing interference.

3.3 EPS for Resource Block Allocation Problems

EPS is an integer programming method for small-scale resource allocation problems. In multi-slice networks, RB resource allocation is discrete, so it can be modeled as an integer programming problem. The EPS method consists of three phases: enumeration, pruning, and scoring.

The enumeration phase lists all candidate allocation schemes that meet the total resource constraints. The pruning phase eliminates schemes that do not meet the minimum quality of service requirements for a slice (for example, URLLC must obtain contiguous rbs). The scoring phase scores the remaining schemes based on qos completion rate, energy efficiency, and fairness, selecting the one with the highest score.

EPS is suitable for small-scale networks or for initializing the initial NSGA-II population. It can also be used for verification testing under simplified models.

3.4 Construction of Multi-Objective Optimization Framework

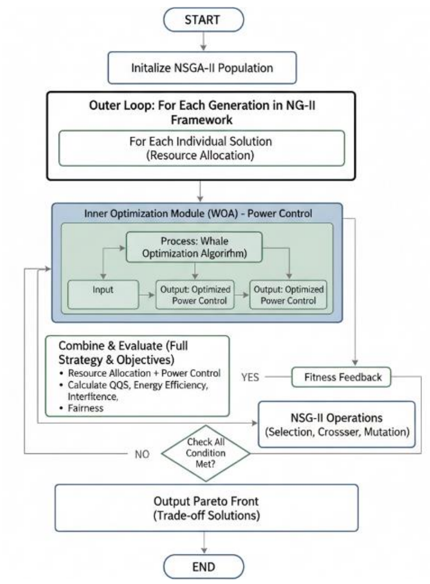

Figure 1: Overall methodological framework

In order to coordinate resource allocation and power control issues under multiple conflicting objectives, this paper constructs a two-layer nested multi-objective optimization framework. The framework is divided into an outer optimization module and an inner optimization module, which work together to achieve efficient search for Pareto optimal solutions. Its structure and process are shown in Figure 1.

4. Experiments and Results Analysis

This chapter experimentally demonstrates the effectiveness of the proposed multi-objective optimization framework for wireless resource management. First, we introduce the experimental setup, including the experimental environment, dataset, and algorithm parameter configuration. Then, we present the experimental results and provide a detailed analysis. Finally, we compare the performance of different algorithms and evaluate their advantages and disadvantages.

4.1 Experimental setup

The experiments were conducted on a multi-core CPU platform using Python, relying on scientific computing libraries such as NumPy, SciPy, and Matplotlib. The experiments were run on a server with 16GB of RAM and a 2.5GHz processor. The algorithm parameters are shown in Table 1.

Table 1: Algorithm Parameters

Algorithm	Population Size	Generations	Crossover Probability	Mutation Probability
NSGA-II	100	200	0.8	0.2
WOA	50	100	nan	nan

Continued Table

Selection Method	Spiral Updating Coefficient	Random Search Probability
Roulette Wheel Selection	nan	nan
None	0.5	0.1

To validate the proposed multi-objective optimization framework, this experiment used a simulation dataset encompassing resource allocation problems in a 5G network environment. The dataset includes 10 base stations, each supporting up to five different service slices (URLLC, embb, and mmtc), each with different quality of service requirements. The total network bandwidth is set to 100 mhz, with a maximum power of 50 W. The system contains 100 users, randomly distributed within the service areas of the 10 base stations.

In the experiment, we simulated different trade-offs between quality of service, energy efficiency, and interference control by adjusting different objective weights. Key performance metrics include:

QOS Completion: The completion rate of each service slice, representing the ratio of actual service volume to required service volume.

System Energy Efficiency: The network service quality per unit of energy consumption, indicating the amount of service the network can deliver with a given energy consumption.

Interference Suppression: The degree to which interference between different base stations within the system is controlled. Lower interference means a more efficient system.

Fairness Index: The Jain index is used to measure service fairness among different users.

4.2 Experimental results

The experiment first conducted optimizations under different objective weighting configurations to study the impact of weight changes on the final results. Figure 2 shows the performance of different weight combinations for quality of service, energy efficiency, and interference mitigation. As can be seen, with higher quality of service weighting, system completion significantly improved, but energy efficiency and interference mitigation decreased. Conversely, with higher energy efficiency weighting, system energy efficiency and interference mitigation improved, but service quality decreased.

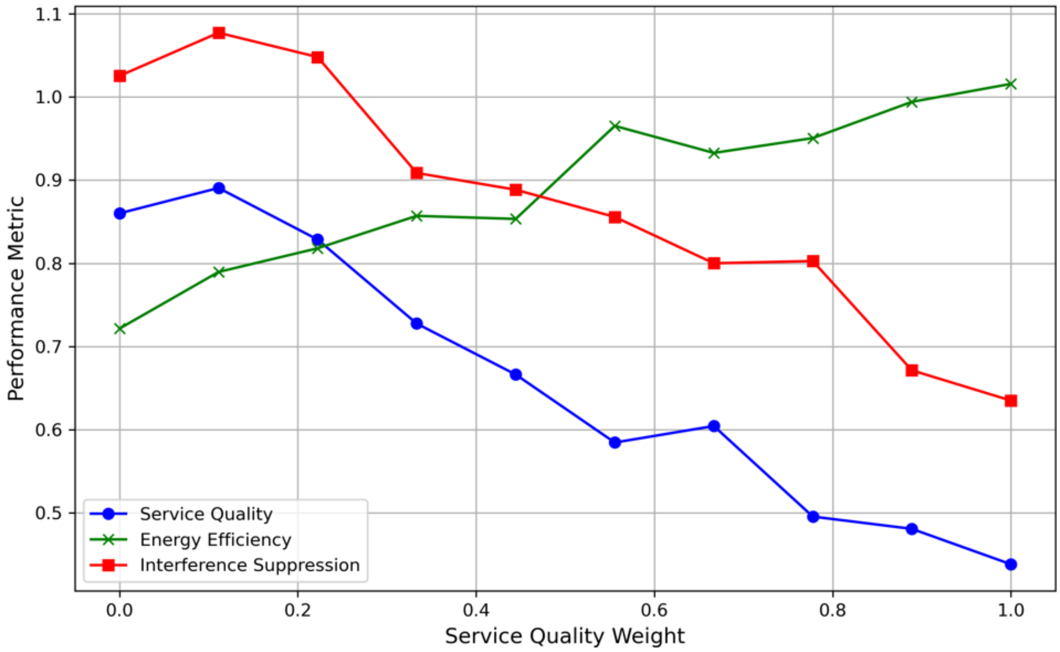

Figure 2: Comparison of optimization results under different objective weights

To validate the performance of the proposed framework, experiments also compared NSGA-II and WOA with the classic genetic algorithm (GA) and particle swarm optimization (PSO), respectively. Table 2 lists the final results achieved by each algorithm during the optimization process, focusing on comparisons of service quality, energy efficiency, and interference suppression.

Table 2: Performance comparison of different algorithms

Algorithm	Service Quality Completion	System Efficiency	Interference Suppression	Fairness Index
NSGA-II + WOA	0.95	0.85	0.9	0.88
GA	0.85	0.75	0.8	0.82
PSO	0.9	0.78	0.85	0.85

As can be seen from the Table 2, the optimization framework combining NSGA-II and WOA demonstrates superior performance across multiple objectives, particularly in terms of system energy efficiency and interference suppression, achieving significant improvements compared to other algorithms.

To further analyze the convergence performance of the algorithms, figure 3 shows the speed at which different algorithms converge to the Pareto front during the optimization process. It can be seen that NSGA-II and WOA converge significantly faster than GA and PSO, especially when dealing with multi-objective problems, and are able to find a reasonable solution set more quickly.

This chapter experimentally validates the effectiveness of the proposed multi-objective optimization framework and compares the performance of different algorithms. The experimental results demonstrate that the optimization framework combining NSGA-II with WOA effectively addresses multi-objective resource allocation problems, achieving a good balance between quality of service, energy efficiency, and interference mitigation. Furthermore, compared with traditional optimization algorithms, this framework exhibits higher performance and better convergence, making it suitable for practical wireless network resource management tasks.

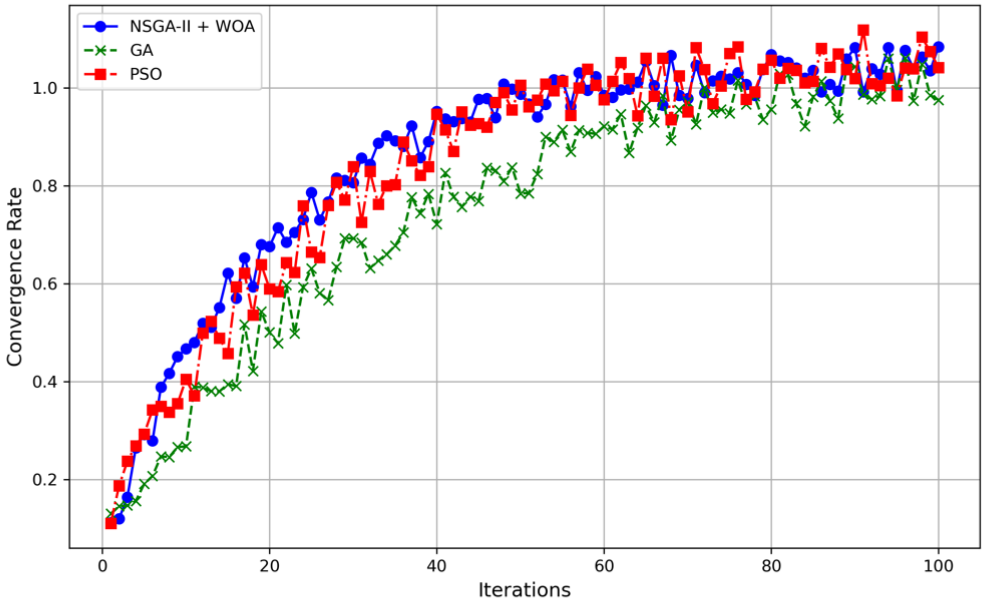

Figure 3: Convergence Comparison of Different Algorithms

5. Conclusion and Outlook

This paper proposes a multi-objective optimization-based radio resource management framework that combines the nsga-II algorithm and the WOA to address resource allocation and power control problems under multi-objective conditions. By optimizing multiple objectives, QOS, energy efficiency, and interference mitigation, this framework effectively balances these conflicts, providing a novel solution for resource scheduling in wireless communication networks.

First, experimental results demonstrate that the proposed optimization framework demonstrates strong performance across multiple objectives. Under varying objective weights, the framework flexibly balances qos, energy efficiency, and interference mitigation. In particular, high qos weighting significantly improves system performance, while high energy efficiency weighting significantly improves system energy efficiency and enhances interference mitigation.

Compared with traditional algorithms, the combination of nsga-ii and woa demonstrates significant advantages. Specifically, the combination of nsga-ii and woa not only improves the system's convergence speed but also enables rapid discovery of optimal solutions in multi-objective optimization. In particular, the combination of global search and local optimization ensures the algorithm's efficiency and accuracy when addressing multi-objective problems.

Finally, this multi-objective optimization framework provides a new approach to radio resource management and power control, enabling optimized resource allocation under multiple constraints. While this research has achieved some results, there is still room for improvement. Future work could consider extending this framework to more complex network scenarios and further investigating resource optimization methods for different service types and dynamically changing conditions.

In summary, the optimization framework proposed in this paper provides effective technical support for resource management and scheduling in next-generation wireless communication networks, and has significant application value in improving the performance of 5G and future 6G networks.

References

[1] H. Cui, F. Cao, and R. Liu, "A multi-objective partitioning algorithm for large-scale graph based on NSGA-II," Expert Syst. Appl., vol. 263, p. 125756, Mar. 2025, doi: 10.1016/j.eswa.2024.125756.

[2] B.-S. Kim, B. Shah, T. He, and K.-I. Kim, "A survey on analytical models for dynamic resource management in wireless body area networks," Ad Hoc Networks, vol. 135, p. 102936, Oct. 2022, doi: 10.1016/j.adhoc.2022.102936.

[3] H. Xu, J. Wang, H. Tang, and X. Yuan, "Efficient parallel scheduling with power control and successive interference cancellation in wireless sensor networks," Ad Hoc Networks, vol. 154, p. 103383, Mar. 2024, doi: 10.1016/j.adhoc.2023. 103383.

[4] Z. Wang, Y. Cao, Z. Chang, T. Lv, and W. Ni, "Energy efficiency maximization in UAV communication networks with nonlinear energy harvesting," Comput. Networks, vol. 241, p. 110222, Mar. 2024, doi: 10.1016/j.comnet.2024.110222.

[5] S. Taimoor, L. Ferdouse, and W. Ejaz, "Holistic resource management in UAV-assisted wireless networks: an optimization perspective," J. Network Comput. Appl., vol. 205, p. 103439, Sep. 2022, doi: 10.1016/j.jnca.2022.103439.

[6] L. R. Frank, A. Galletta, L. Carnevale, A. B. Vieira, and E. F. Silva, "Intelligent resource allocation in wireless networks: predictive models for efficient access point management," Comput. Networks, vol. 254, p. 110762, Dec. 2024, doi: 10.1016/j.comnet.2024.110762.

[7] G. Subrahmanyam, M. Puttaramaiah, G. Kalnoor, and P. B. Metre, "Joint radio resource management soft computing technique for 5G and beyond 5G wireless networks," 20th Int. Conf. Future Netw. Commun./ 22nd Int. Conf. Mob. Syst. Pervasive Comput./15th Int. Conf. Sustain. Energy Inf. Technol. (fnc/mobispc/seit 2025), vol. 265, pp. 17–24, Jan. 2025, doi: 10.1016/j.procs.2025.07.151.

[8] M. Verma, U. Rathore Bhatt, R. Upadhyay, and V. Bhat, "MLGO: a machine learning-based mountain gazelle optimization algorithm for efficient resource management and load balancing in fiber wireless access networks," Opt. Fiber Technol., vol. 88, p. 104014, Dec. 2024, doi: 10.1016/j.yofte.2024.104014.

[9] Q. Wang, K. Cai, Z. Qin, and Z. Guan, "Multi-objective optimization of laminated structures for central cone based on NSGA-II genetic algorithm," Int. J. Heat Mass Transfer, vol. 253, p. 127531, Dec. 2025, doi: 10.1016/j. ijheatmasstransfer. 2025.127531.

[10] M. S. Singh and R. Pasumarthy, "Optimal power allocation in wireless communication networks using stochastic control," 3rd Control Conf. Afr. CCA 2024, vol. 58, no. 25, pp. 186–191, Jan. 2024, doi: 10.1016/j.ifacol.2024.10.259.

[11] Y. Liao, H. Zhou, C. Leng, Z. Su, and T. Qin, "Power control and task offloading strategies for high-density wireless body area networks based on deep reinforcement learning," Comput. Networks, vol. 267, p. 111351, Jul. 2025, doi: 10. 1016/j.comnet.2025.111351.

[12] D. Damodaram, R. K. Godi, Rajkumar, D. V. Divakara Rao, K. B. Glory, and K. Somu, "Power control management system model using wireless sensor network," Meas.: Sens., vol. 25, p. 100639, Feb. 2023, doi: 10.1016/j.measen.2022. 100639.

[13] H. Dutta, A. K. Bhuyan, and S. Biswas, "Reinforcement learning based flow and energy management in resource-constrained wireless networks," Comput. Commun., vol. 202, pp. 73–86, Mar. 2023, doi: 10.1016/j.comcom.2023.02.011.

[14] A. I. Maass, D. Nešić, R. Postoyan, V. S. Varma, S. Lasaulce, and D. Muñoz-Carpintero, "Transmit power policies for stochastic stabilisation of multi-link wireless networked control systems," Automatica J. IFAC, vol. 171, p. 111936, Jan. 2025, doi: 10.1016/j.automatica.2024.111936.

[15] G. S. Kori, M. S. Kakkasageri, P. M. Chanal, R. S. Pujar, and V. A. Telsang, "Wireless sensor networks and machine learning centric resource management schemes: a survey," Ad Hoc Networks, vol. 167, p. 103698, Feb. 2025, doi: 10.1016/j.adhoc.2024.103698.